

Predicting agricultural impacts of large-scale drought: 2012 and the case for better modeling

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Introduction

The 2012 growing season saw one of the worst droughts in a generation in much of the United States. A warm, dry winter ended early and abruptly with an extraordinary heat wave in March that left soils parched in much of the country. A hot spring and hotter summer, punctuated by a near-unprecedented hot June, left many crops stunted and heat stressed. Sustained hot conditions significantly accelerated crop development stages, and continued hot dry conditions through July meant plant stress during key stages around flowering in much of the Corn Belt [1]. Drought extent finally peaked in September, at which point 65.45% of the contiguous United States was experiencing drought conditions according to the U.S. Drought Monitor [2].

Droughts in Europe, the worst in several decades in some regions, and in Russia kept U.S. export demand high and emphasized the importance of a global perspective for U.S. agricultural policy and commercial interests [3]. More than any other season in recent memory, 2012 has cast a harsh light on the need for better analytic tools and a comprehensive approach to predicting and preparing for the effects of extreme weather on agriculture.

We present here an example of a simulation-based forecast for the 2012 U.S. maize growing season produced as part of a high-resolution, multi-scale, predictive mechanistic modeling study designed for decision support, risk management, and counterfactual analysis. The simulations undertaken for this analysis were performed in December 2012 using weather data up to and including November 30 2012, making it less a forecast of the harvest itself (which was largely completed before this date) than a forecast of the official county-level

statistics of the 2012 harvest, scheduled for release on February 21, 2013 [4]. The presence of useful predictive information in a zero lead time forecast such as this is a necessary, although obviously not sufficient, condition of a framework's ability to provide useful predictive information at longer lead times.

Broadly speaking, our goal in presenting this study is to demonstrate an improved multi-model simulation framework that can contribute to an understanding of where and how extreme conditions negatively impact U.S. agriculture. Such an understanding can help scientists, policy-makers, and stakeholders elucidate farm- and system-level changes that could be implemented in order to mitigate the impacts of similar droughts in the future. By presenting forecasts of 2012 county-, state-, and national-level maize yields before the official county-level statistics are reported by the USDA, we provide a basis for subsequent critical evaluation of the framework's ability, with current technology, data, and models, to forecast the agricultural impacts of extreme weather. In so doing, we also contribute to understanding the validity of dynamic process crop models for assessing the impacts of a hotter future on agriculture as a result of climate change.

Predictive forecasts at any scale must address four basic properties: **validation**, **uncertainty**, **credibility**, and **clarity**. For example, the hindcasts presented here are **validated** against NASS statistics at the county, state, and national level and will be the subject of a subsequent peer-reviewed and publicly accessible validation study. To characterize and communicate the **degree of certainty** in our forecasts explicitly, we express predictions at each scale probabilistically

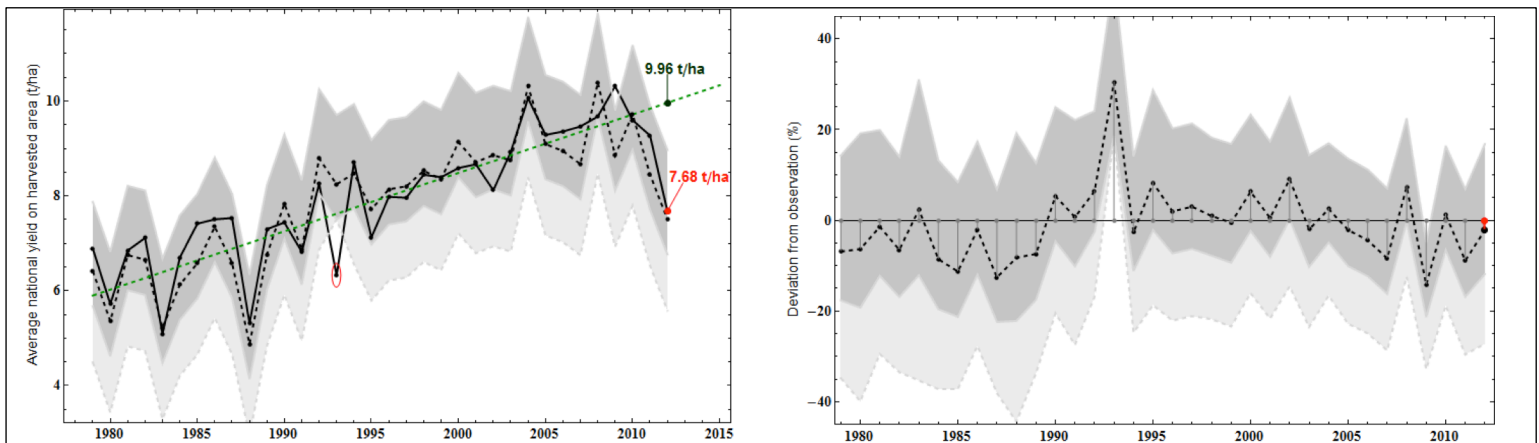


Fig 1: Left: Simulated (dashed line and points), observed (solid line and points), and observed linear trend (dashed straight green line) of national average maize yield in metric tons per hectare from 1979–2012. The red dot indicates a USDA estimate for 2012 that has not yet been finalized. Gray shading indicates the cross-validated 95% confidence interval around the forecast. One year falls far outside this interval (circled in red): in 1993 excessive rainfall led to water-logged soils throughout much of the Midwest, causing root death and reduced growth [5]. We have made no attempt to capture this effect in the simulations described here since we are primarily interested in the effects of heat and drought. For this reason, we show the cross-validated confidence interval both without (darker band, solid border) and with (lighter band, dashed border) this year included in our uncertainty analysis. **Right:** Deviation from observed of the simulated national maize yield as a percent of the observation in each year. The red dot and line indicate that the “observational value” used for 2012 is an estimate that is not yet official.

based on model performance in the preceding years (Fig. 1). To establish our approach as **credible**, for example, we are publishing zero lead time county-, state- and national-level forecasts of U.S. maize yields for the 2012 season [6], complemented by hindcasts from 1979 to 2011 (Fig. 1), ahead of official county-level statistics. The final essential property of a good prediction is that it be communicated to stakeholders in a way that provides **clear and actionable information** about risks and outcomes. Elements essential for prediction clarity include (a) clearly defined assumptions, (b) expression of results in terms of decision-relevant metrics familiar to stakeholders, and c) risk communication through simple but robust probabilistic measures of uncertainty.

For example, the USDA released in February 2013 their annual report on long-term agricultural projections (for 2013-2022) [7]. Despite substantial variability in actual maize yields around the linear trend over the past 30 years (e.g., see Fig. 1), the report assumes that yields in 2013 will revert back to the linear trend and describes expected production over the next decade deterministically (i.e., it does not provide uncertainty estimates). A consequence of such reports is media coverage such as the following:

U.S. corn output is projected to increase 34% to 14.4 billion bushels in the 2013-14 season, the USDA said yesterday in a 10-year forecast. – Bloomberg News 02/12/13 [8]

This is clearly a misreading of the report, which is meant to provide a long-term baseline for agricultural production and trade rather than a prediction for next year's harvest. Such miscommunications could be minimized given clear explanation of the assumptions, uncertainties, and appropriate uses of future forecasts.

The model, inputs, and results

We have undertaken a high-resolution mechanistic model-based assessment of the 2012 growing season in the United States. The modeling framework used here is called the parallel System for Integrating Impacts Models and Sectors (pSIMS). At the core of this system is the process-based crop model CERES-Maize, distributed as part of the Decision Support System for Agrotechnology Transfer (DSSAT) [9]. Simulations are performed at 5-arcminute spatial resolution (about 10 km) and driven by input data at a variety of spatial and temporal scales including

- daily time-series of key weather variables spanning January 1, 1979 to November 30, 2012, from the North American Regional Reanalysis [10];
- soil profiles estimated from the Harmonized World Soils Database [11];
- observed planting and maturity dates and planting densities from the USDA crop progress reports released weekly during the growing season for many decades, generally at the resolution of states or crop reporting districts,

- county-level data from 1979 to 2011 on irrigated and rainfed harvested areas from the USDA NASS; and
- estimates of the distribution of land and management practices at the subcounty level from the Spatial Production and Allocation Model dataset [12].

Simulations are performed everywhere in the conterminous United States for rainfed and irrigated maize, with 2 cultivars chosen based on the recent local history of growing degree units, and 5 planting dates (the dates at which 10, 30, 50, 70 and 90% of the crop is reported to be planted in each year according to the USDA crop progress reports). The results are then aggregated to the county level and compared with survey-based historical observations of yields from the USDA NASS to estimate cross-validated confidence intervals as in Fig. 1 and validate the overall forecast. Results indicate that the drought damage was fairly well distributed across the major grain-producing regions of the country, with the worst-hit areas in the Midwest (Fig. 2).

We estimate national average yields of 7.507 t/ha for 2012, 24.6% below the expected value based on increasing trend yield alone, with a 95% confidence interval based on historical model performance (not including 1993) stretching from 6.768 to 8.967 t/ha (Fig. 1) (the lower bound on the confidence interval is 5.586 with 1993 included in the analysis). On average, the median yield simulations deviate from NASS observations by 8.3% from 1979 to 2011 (6.5% without including 1993). For comparison, the USDA releases a national maize yield forecast every month starting in early August of each year (with the last forecast released in November), based on surveys of kernel counts and weights from fields around the country. In 2012, the USDA August forecast for National average maize yield was 7.746 t/ha, which was revised down twice to 7.658 t/ha in October before being tweaked up to 7.676 t/ha in November (the red dot in Fig. 1).

Mechanistic models have the added benefit of being capable of simulating counterfactual scenarios in order to explore the major causes and potential ameliorating factors of extreme events. For example, in addition to the basic hindcast and zero lead time forecast, we performed a simple counterfactual experiment to characterize the similarities and differences between 2012 and 1988, the most recent comparable drought year. To do so, we swapped the observed weather for 1988

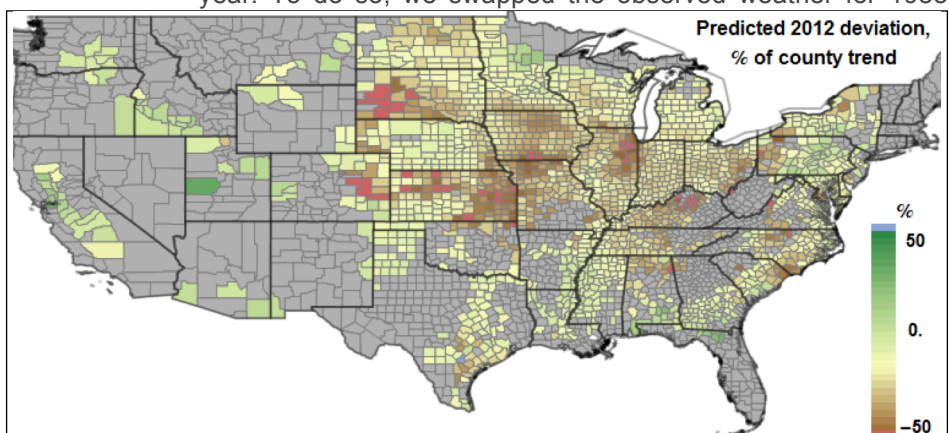


Fig 2: Median deviation of simulated county-level yields from linear trend as a percentage of county-specific trend yield from 1979 to 2011 (extrapolated to 2012). Only counties with at least 500 ha of maize harvested in 2011 are shown.

and 2012 and ran the simulations with all else equal. The findings indicate that, even though the losses in 1988 relative to trend were more severe (30.1% loss relative to trend, compared to 24.6% in 2012), the weather in 2012 was actually far worse. According to the counterfactual simulations, if weather in 1988 had matched what we saw in 2012, losses would have approached 37.2% of trend. Similarly, the scenario indicates that if the 2012 season had seen weather like 1988, losses relative to trend would have been only 13.4%.

These results imply that system-level changes and adaptations have occurred since 1988 that could be used to improve further drought-response strategies. Counterfactual simulations can also be used to quantify the benefits of system-level management and technology changes, such as increased water retention and irrigation, which have the potential for substantial contributions to risk management and adaptation planning.

Discussion

Hot and dry conditions during the 2012 growing season led to devastating crop losses in much of the country, and likely the worst U.S. maize harvest (relative to the increasing yield trend) since at least 1988. Investments in modern assessment, planning, and decision-support tools that can provide actionable local information within a global context that satisfies the four principles of validation, uncertainty, credibility, and clarity could improve risk assessment, increase lead times for decisions at seasonal to multidecadal timescales, and help stakeholders prepare for a warmer climate as global temperatures continue to rise. Continued advances, such as improved tracking of drought and climate change effects, require better metrics for measuring drought and heat events, long-running programs for monitoring climate change effects in agriculture, and tools for identifying hotspots as they emerge.

While better monitoring and modeling can help us prepare for these events by mitigating and managing our risk and exposure, forecasting tools developed in concert with farm management practices will foster more effective risk management. Drought tolerance, for example, can be improved by changes in farming methods from the field scale to the

system scale, such as more investment in tolerant hybrids, efficient irrigation technologies that leverage sustainable water resources and minimize ground water depletion, low-till and no-till farming, and improved soil water retention through cover crops and smart fallow management.

Forecasts, ideally probabilistic forecasts, from systems such as the one presented above can play a significant role in improving modern crop-risk management, reducing losses, and increasing returns. For forecast tools to remain relevant and credible, whether based on mechanistic or on empirical models (or a combination of the two), they must be open and accepting of the limitations and uncertainties in their frameworks and strive to continuously evaluate and improve their underlying components and methodologies.

In the present analysis, we found that the model missed the observations significantly in some years, while estimating other years very accurately. Mechanistic models have the advantage, relative to empirical models, that they can be used for counter-factual analysis; when and where forecasts with mechanistic models go wrong (or right), they can be used to understand why the forecast went wrong (right) and, with some examination, often even indicate what it is about the system that one doesn't (or does) understand. Subsequent analysis of these results will study these outcomes.

Droughts and other climate extremes call for a comprehensive approach to monitoring, modeling, and predicting growing seasons globally by using a combination of statistical models, real-time satellite observations, and high-resolution process-based models. Learning from the successes of weather forecasting, researchers need to bring together data and models in a probabilistic framework that leverages real-time data and high-performance computing to improve risk assessment for a range of scales, such as demonstrated here.

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